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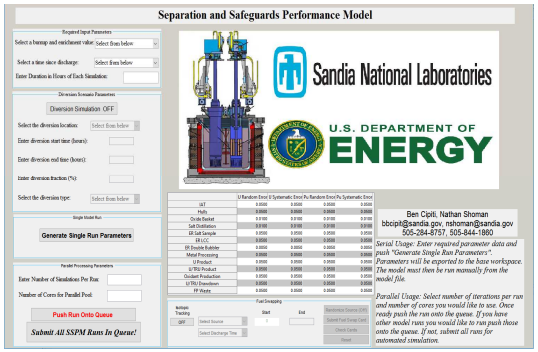

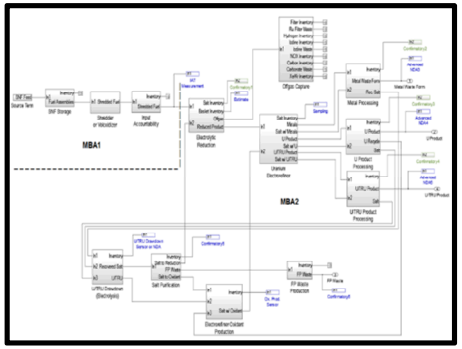

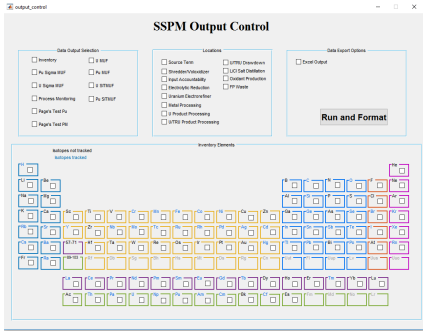

Updates to Statistical Tests and New Capabilities in the Separation and Safeguards Performance Model (SSPM)

Ben Cipiti & Nathan Shoman

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Acknowledgement

- This work has been funded by the Fuel Cycle Technologies program in the U.S. Department of Energy Nuclear Energy and National Nuclear Security Administration program areas.

Outline

- Overview of the Separation and Safeguards Performance Model (SSPM) and applications
- Model updates
- Expansion to the statistical tests
- Example results
- Machine learning

SSPM Overview

- The SSPM is based in MATLAB Simulink. Material flows are tracked for bulk processing facilities, and measurements are simulated for safeguards. PUREX, UREX+, Pyroprocessing, Enrichment versions exist (and soon Molten Salt Reactor).
  - Spent fuel source term library for user-defined runs
  - Mass tracking of elements 1-99, isotopics tracking, bulk solid & liquid, heat load & activity
  - Integration with separations codes (SEPHIS-ORNL and AMUSE-ANL) has been applied in the past
  - Customizable measurements with user-defined measurement error
  - Automated calculation of material unaccounted for (MUF) and error propagation in real-time
  - Various statistical tests and alarm conditions
  - User-defined diversion scenario analyses
  - Integration with process monitoring and physical protection systems.

GUI used to Initiate a Model Run

Separation and Safeguards Performance Model

Required Input Parameters

Select a burnup and enrichment value: Select from below

Select a time since discharge: Select from below

Enter Duration in Hours of Each Simulation:

Diversion Scenario Parameters

Diversion Simulation OFF

Select the diversion location: Select from below

Enter diversion start time (hours):

Enter diversion end time (hours):

Enter diversion fraction (%):

Select the diversion type: Select from below

Single Model Run

Generate Single Run Parameters

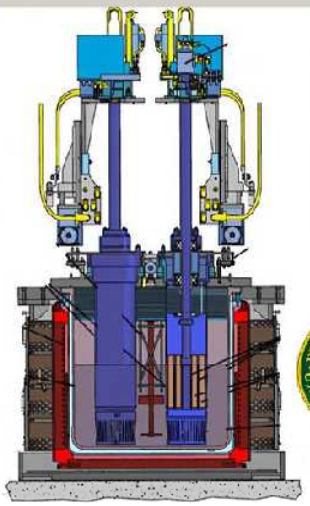
Parallel Processing Parameters

Enter Number of Simulations Per Run:

Number of Cores for Parallel Pool:

Push Run Onto Queue

Submit All SSPM Runs In Queue!



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	U Random Error	U Systematic Error	Pu Random Error	Pu Systematic Error
IAT	0.0500	0.0500	0.0500	0.0500
Hulls	0.0500	0.0500	0.0500	0.0500
Oxide Basket	0.0100	0.0100	0.0100	0.0100
Salt Distillation	0.0100	0.0100	0.0100	0.0100
ER Salt Sample	0.0500	0.0500	0.0500	0.0500
ER LCC	0.0500	0.0500	0.0500	0.0500
ER Double Bubbler	0.0050	0.0050	0.0050	0.0050
Metal Processing	0.0500	0.0500	0.0500	0.0500
U Product	0.0500	0.0500	0.0500	0.0500
U/TRU Product	0.0500	0.0500	0.0500	0.0500
Oxidant Production	0.0500	0.0500	0.0500	0.0500
U/TRU Drawdown	0.0500	0.0500	0.0500	0.0500
FP Waste	0.0500	0.0500	0.0500	0.0500

Fuel Swapping

Isotopic Tracking: OFF

Select Source

Select Discharge Time

Start: 0

End

Randomize Source (Off)

Submit Fuel Swap Card

Check Cards

Reset

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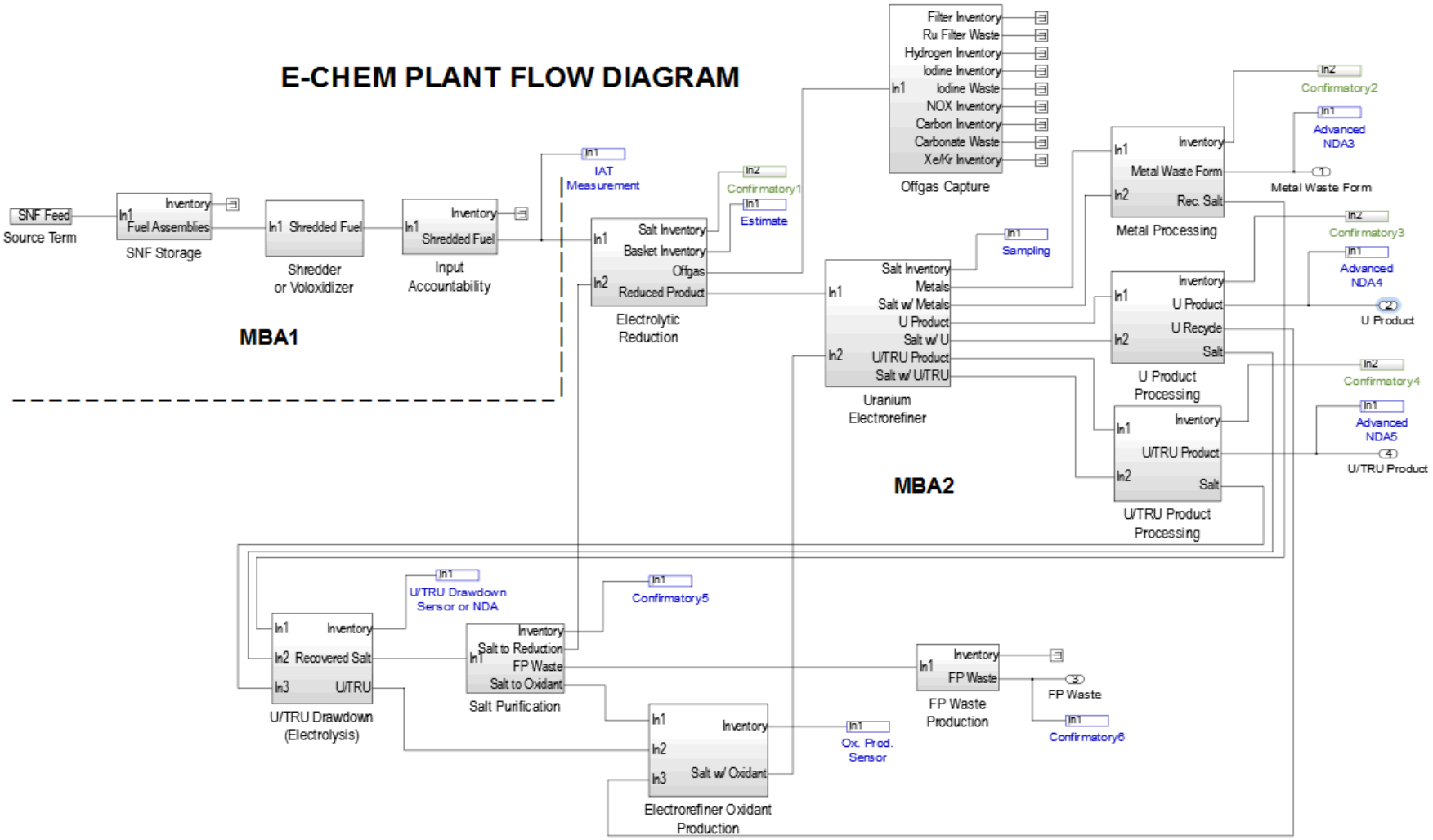
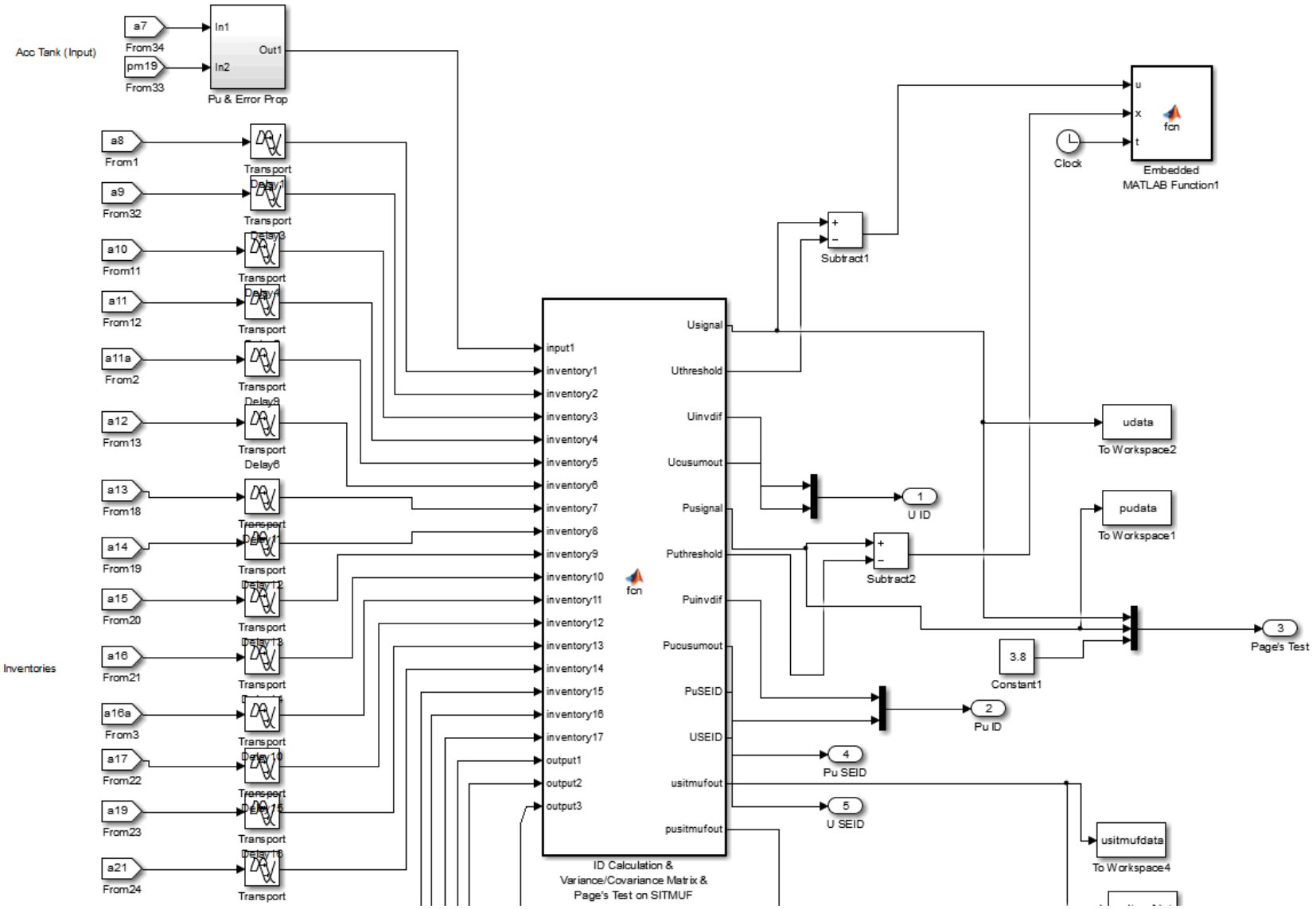
Serial Usage: Enter required parameter data and push "Generate Single Run Parameters". Parameters will be exported to the base workspace. The model must then be run manually from the model file.

Parallel Usage: Select number of iterations per run and number of cores you would like to use. Once ready push the run onto the queue. If you have other model runs you would like to run push those onto the queue. If not, submit all runs for automated simulation.

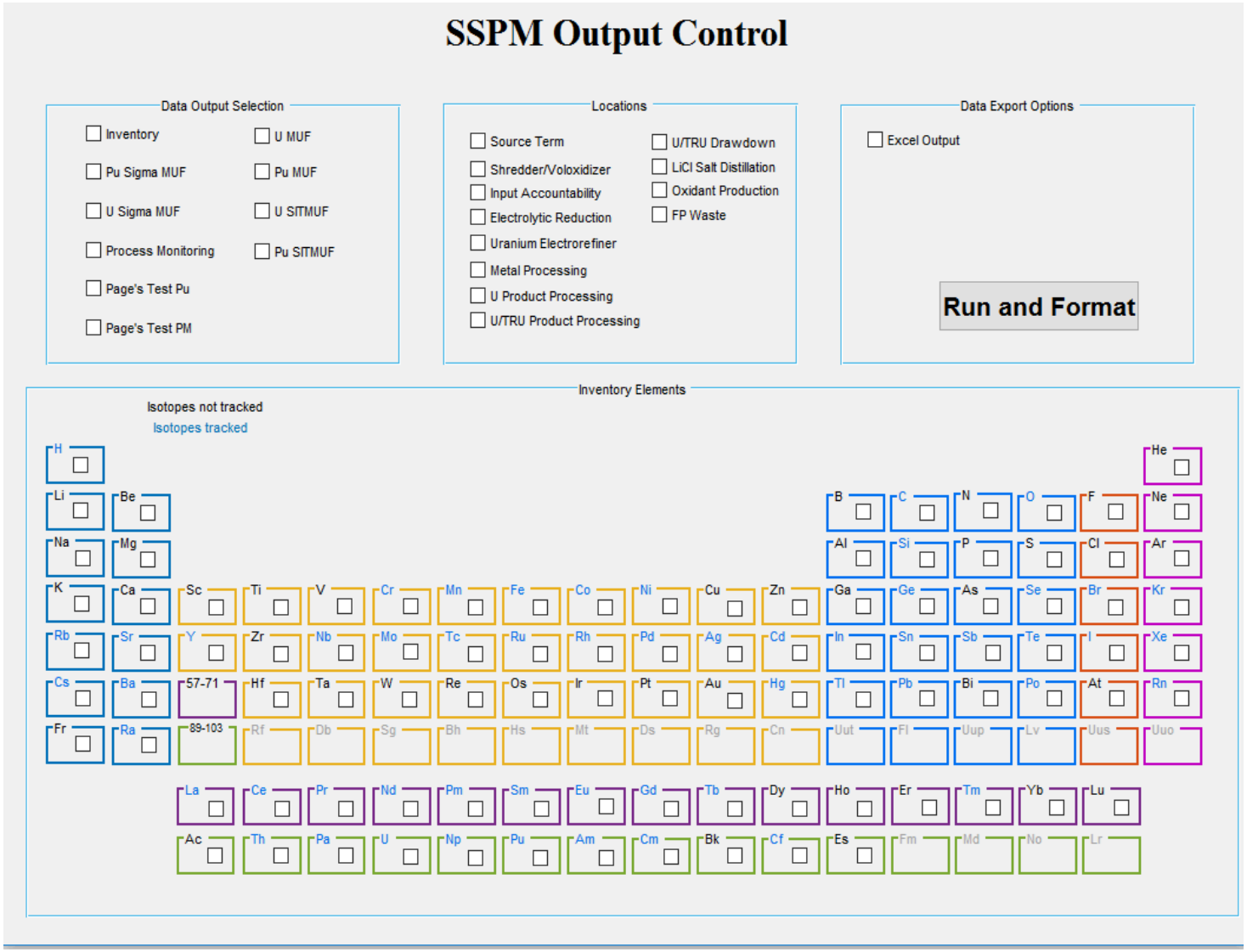
SSPM Pyroprocessing Model



Material Balance Calculation



Output Control



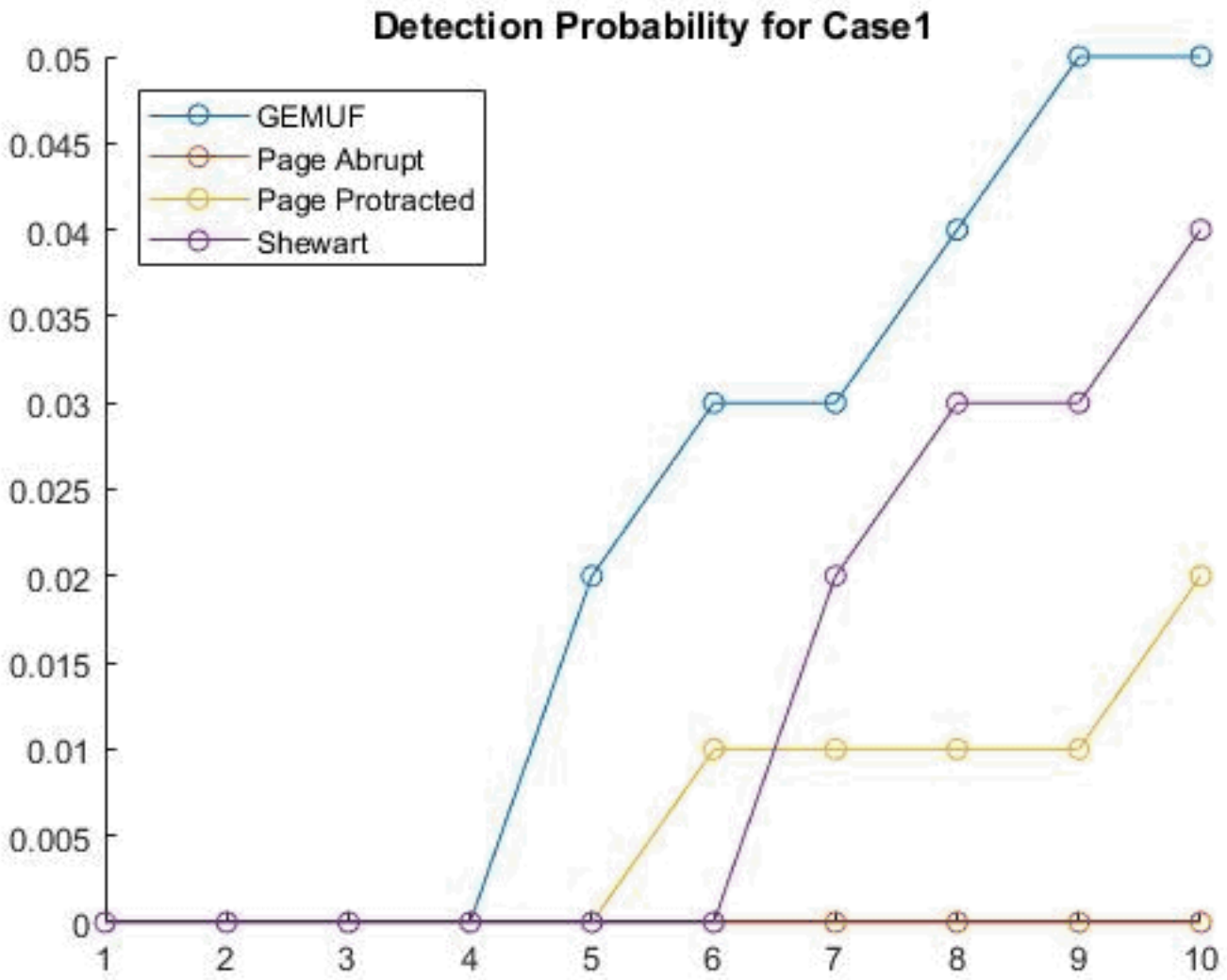
Statistical Tests

- The statistical tests in the SSPM have been expanded to automatically calculate MUF, σ_{MUF}, SITMUF, Shewart test on MUF, Joint Page's test on SITMUF, and GEMUF.
- Recent work has evaluated the performance of these tests in comparison to one another under various diversion scenarios.
- The following slides will show the results under the following scenarios (All runs on generic pyroprocessing plant, 100 MT/yr throughput, 30 day balance period, all loss cases assume total of 8 kg of Pu removed):
  - Case 1: No loss
  - Case 2: Abrupt loss during 3rd balance period
  - Case 3: Protracted loss spread over 3rd and 4th balance periods
  - Case 4: Protracted loss spread over 3rd, 4th, and 5th balance periods
  - Case 5: Protracted split loss between periods 3 and 4 and then 6 and 7

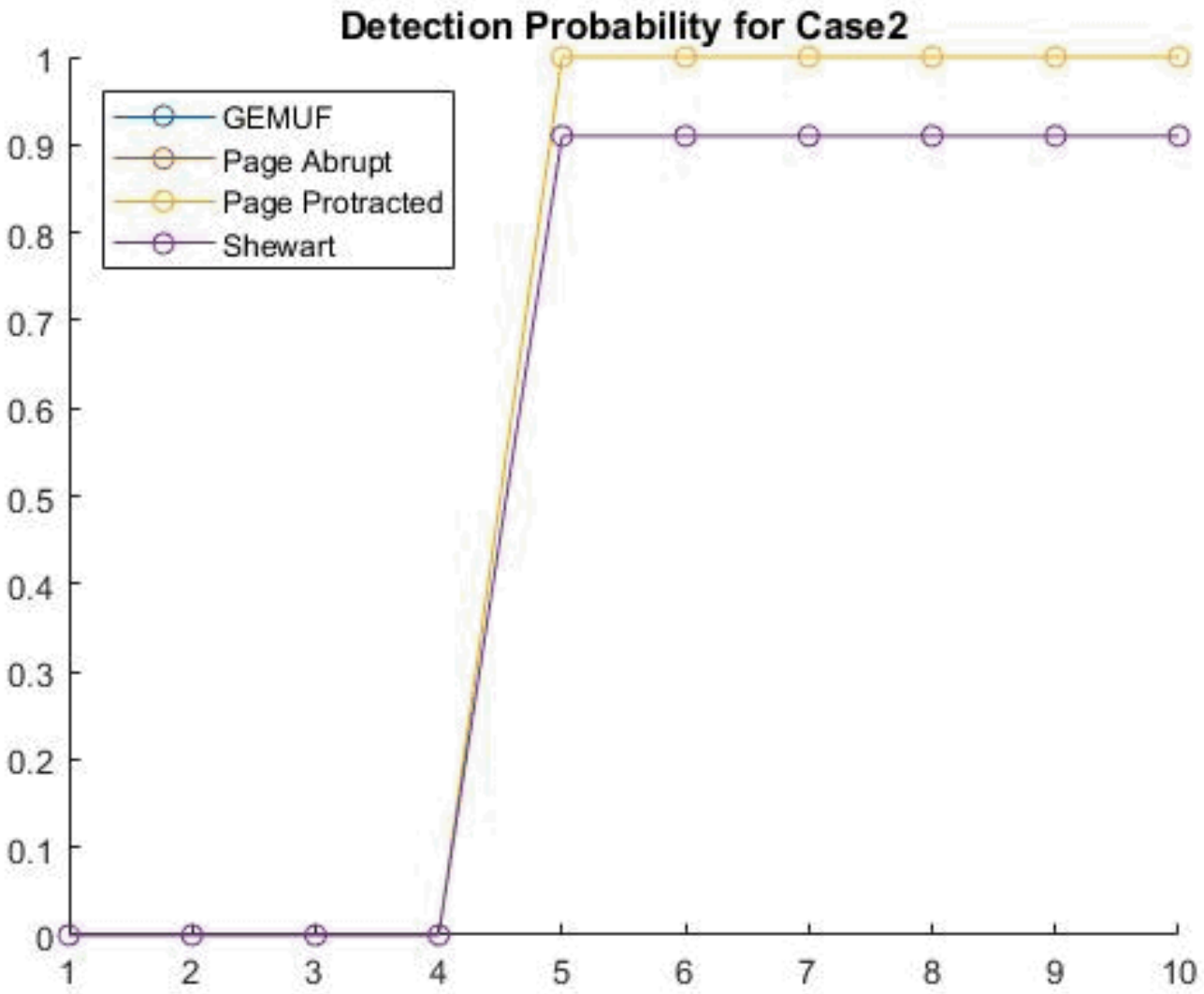
Test Parameters

- Shewart test was applied to MUF values:
  - Alarm condition when any MUF value was greater than 3σ, and 2 out of three consecutive values greater than 2σ, or and 4 out of 5 consecutive values greater than 1.1σ. (set so that FAP ~ 5% per year)
- Page's abrupt test alarm condition:
  - SITMUF > 2.8 (or k=2.8, h=0) (set so that FAP ~ 1% per year)
- Page's protracted test on SITMUF:
  - k=0.5, h= 3.8 (set so that FAP ~ 4% per year)
- GEMUF test variables:
  - 6+x*8/10 (set so that FAP =5% per year)

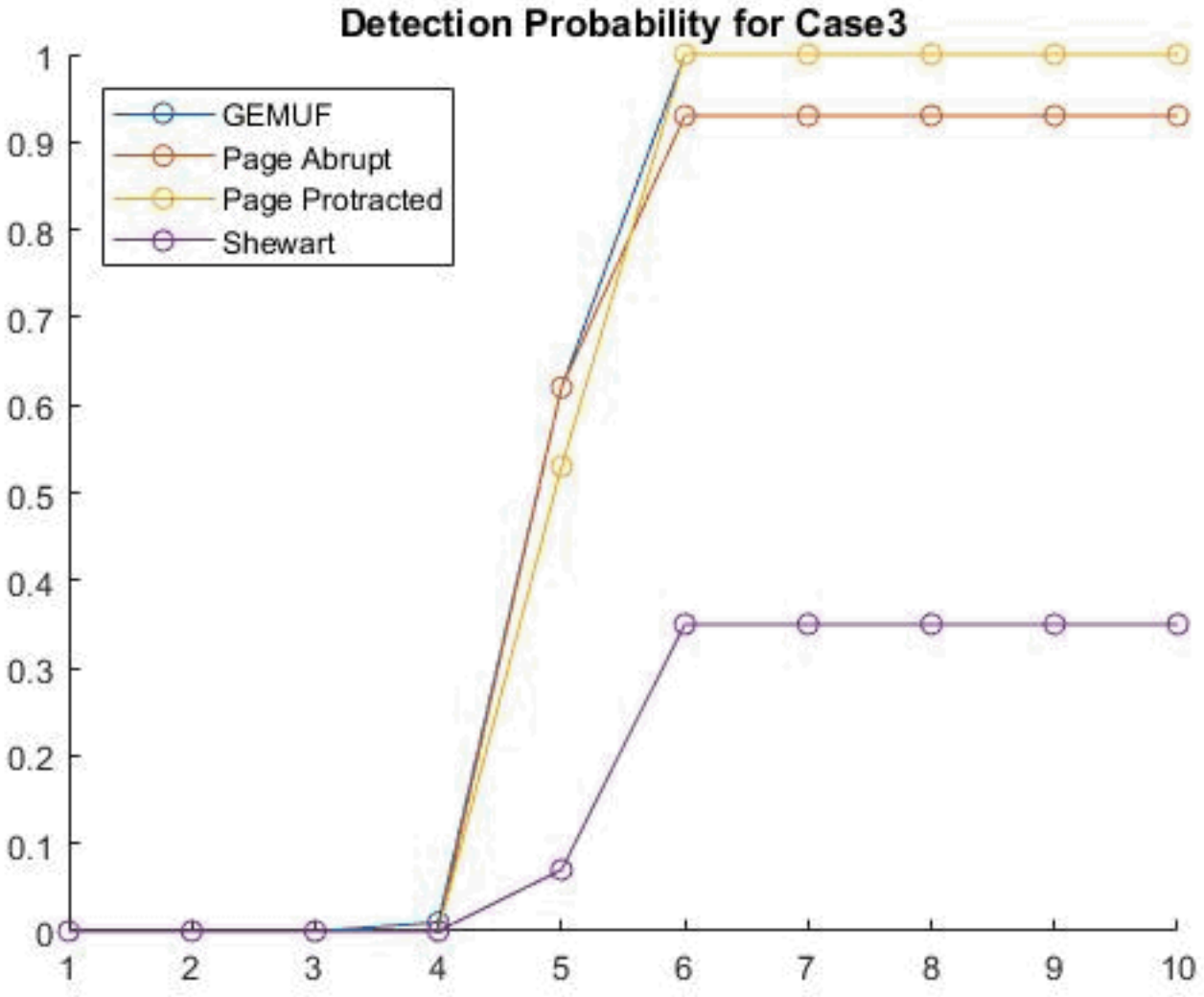
Statistical Test Comparison (No loss)



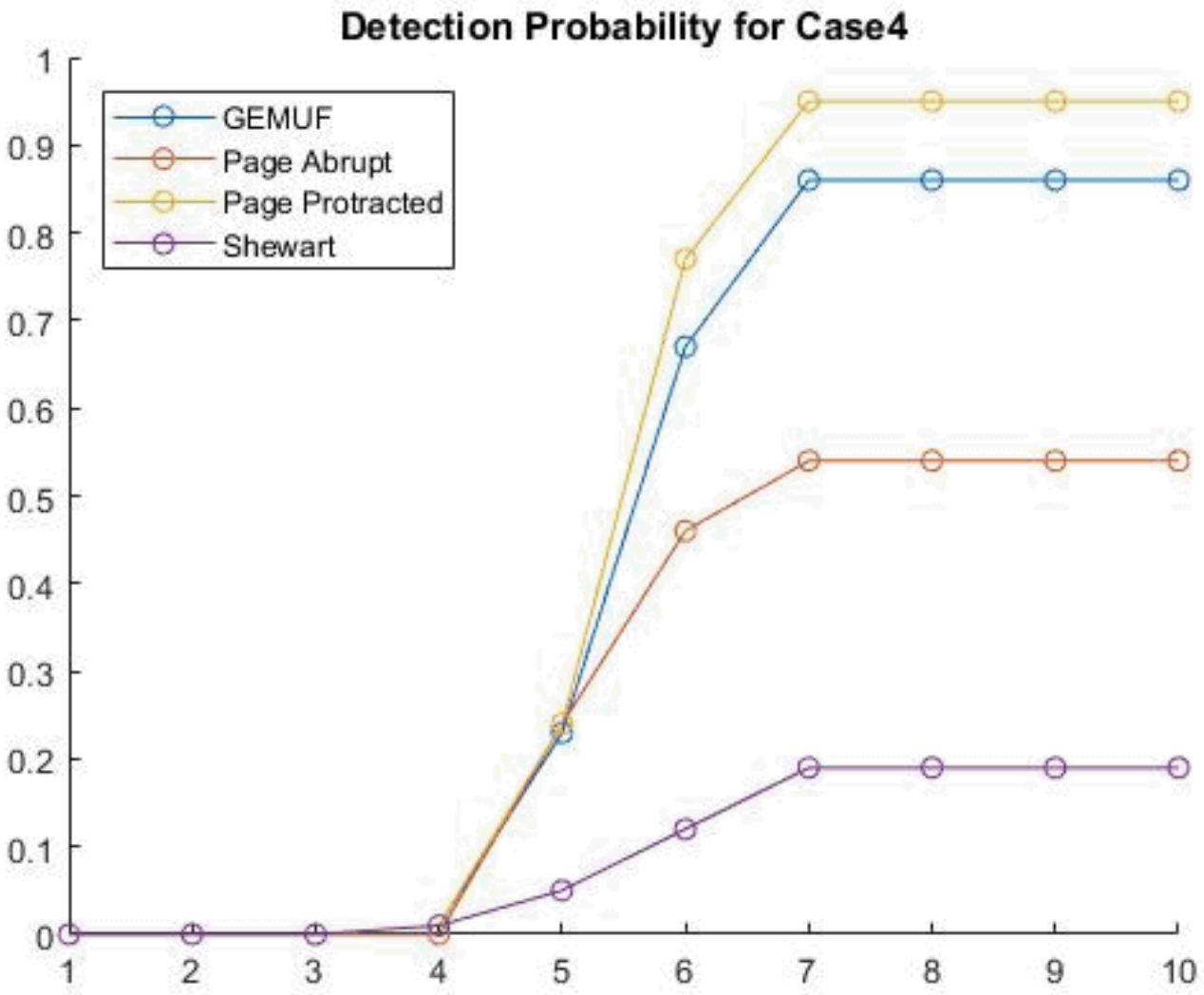
Statistical Test Comparison (Abrupt Loss)



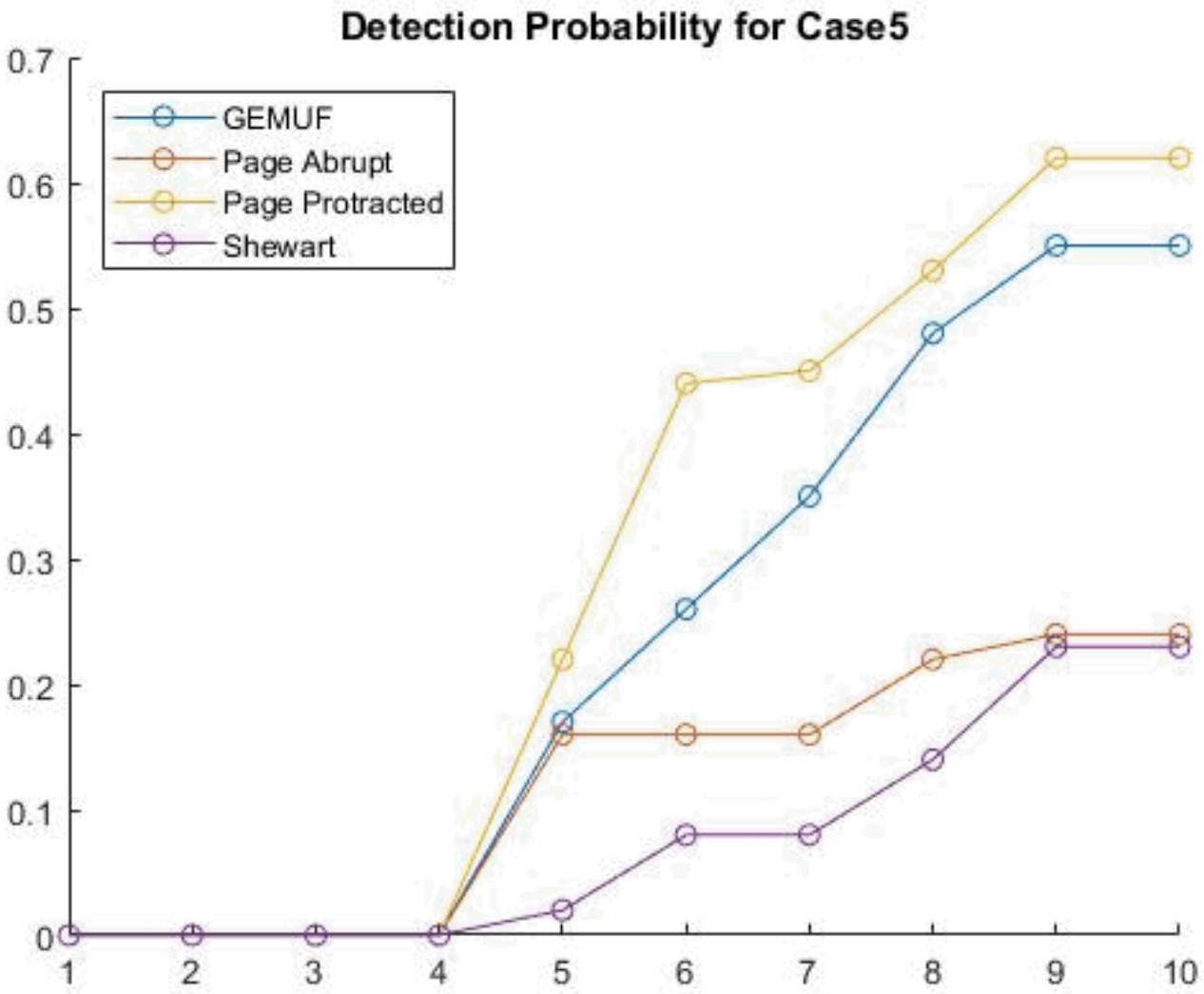
Statistical Test Comparison (Protracted Loss over 2 Balance Periods)



Statistical Test Comparison (Protracted Loss over 3 Balance Periods)



Statistical Test Comparison (Split, Protracted Loss)



Statistical Test Summary

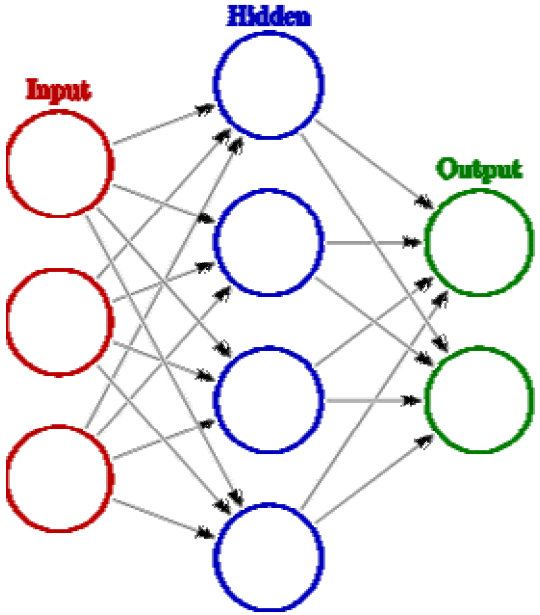
- Based on the comparison shown here, it has increased our confidence in relying on the joint Page's test for the majority of our analysis work.
- However, the model allows us to do all the calculations and various tests at the same time in case other data is needed.
- I have found one of the difficulties of Page's test of SITMUF is explaining it to non-subject matter experts—it's difficult to explain the benefit if the concept is non-intuitive.

Machine Learning

- We are currently exploring the use of the model for generation of training data for machine learning techniques, and applying those techniques as alternative safeguards approaches.
- Supervised learning techniques require large and robust data sets that can be provided by the SSPM:
  - Bulk mass, elemental, isotopic, and spectral data (work in progress)
  - These techniques include linear regression, logistic regression, neural networks, support vector machines, and more.
- Unsupervised techniques can be tested against an array of diversion and upset scenarios
  - These techniques do not rely on labels to determine is an event is anomalous
  - Includes K-means, Principle Component Analysis (PCA), anomaly detection

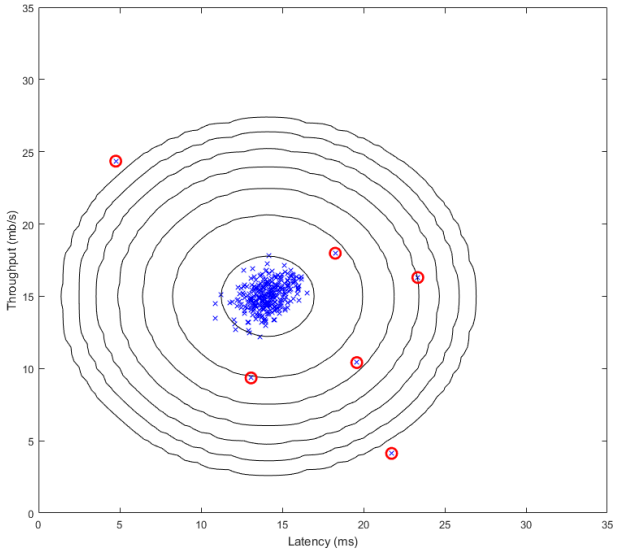
Supervised Techniques

- These techniques seem less applicable to detection of diversion or misuse.
  - Requires learning from labeled training data which means training sets of many possible diversion scenarios. Modeling could help with that, but extremely difficult to get this training data on an actual facility.
- May be more applicable to analysis of open source data
  - For example, Sandia is using Neural Networks to classify open source data for safeguards analysis.
  - Applicable for image recognition.



Unsupervised Techniques

- These techniques seem more applicable to detection of diversion or misuse.
  - Relies on the underlying data structure or statistical tests, and does not need examples of all upset conditions. (However, still requires training data for normal operation.)
- We're interested in Anomaly/Outlier Detection for materials accountancy and detection of misuse.
  - Density-based techniques, cluster analysis, and statistical tests are used to detect outliers.
  - Requires few to no examples of outliers.



Pyroprocessing Example

- Pyroprocessing may have higher uncertainties for Input Accountancy, and better measurements of the electrorefiner salts and products. How can we better use process monitoring data to provide assurance?
- Machine Learning may be used to correlate various data streams:
  - Overall Pu balance (limited by IAT uncertainty)
  - Bulk mass balances for OR, ER, product processing steps (operator data only??)
  - NDA confirmatory measurement of all U products
  - Current, voltage monitoring for both cathodes.
- The key is to **quantify how or if all of this data provides more assurance** than using the Pu balance alone.

Summary

- The SSPM provides a platform for numerous types of safeguards analyses.
- Recent model updates have focused on improving the user interface, expanding capabilities, and standardizing the model outputs when data is needed for other researchers.
- The statistical test comparison continues to give us confidence in the use of a joint Page's test for use in diversion scenario analysis.
- Future work will expand on the use of the model to inform machine learning and potentially provide new safeguards approaches.